

Extending Feynman's Formalisms for Modelling Human Joint Action Coordination

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Abstract

The recently developed Life-Space-Foam approach to goal-directed human action deals with individual actor dynamics. This paper applies the model to characterize the dynamics of co-action by two or more actors. This dynamics is modelled by: (i) a two-term joint action (including cognitive/motivational potential and kinetic energy), and (ii) its associated adaptive path integral, representing an infinite-dimensional neural network. Its feedback adaptation loop has been derived from Bernstein's concepts of sensory corrections loop in human motor control and Brooks' subsumption architectures in robotics. Potential applications of the proposed model in human-robot interaction research are discussed.

Keywords: Psycho-physics, human joint action, path integrals

1 Introduction

Recently [1] we have suggested a generalized motivational/cognitive action, generating Lewinian force-fields [2, 3] on smooth manifolds. On the other hand, cognitive neuroscience investigations, including fMRI studies of human co-action, suggest that cognitive and neural processes supporting co-action include joint attention, action observation, task sharing, and action coordination [4, 5, 6, 7]. For example, when two actors are given a joint control task (e.g., tracking a moving target on screen) and potentially conflicting controls (e.g., one person in charge of acceleration, the other – deceleration), their joint performance depends on how well they can anticipate each other's actions. In particular, better coordination is achieved when individuals receive real-time feedback about the timing of each other's actions [7].

2 The Action-Amplitude Model

To model the dynamics of the joint human action, we associate each of the actors with an n -dimensional (n D, for short) Riemannian Life-Space manifold, that is a set of their own time dependent trajectories, $M_\alpha = \{x^i(t_i)\}$ and $M_\beta = \{y^j(t_j)\}$, respectively. Their associated tangent bundles contain their individual n D (loco)motion velocities, $TM_\alpha = \{\dot{x}^i(t_i) = dx^i/dt_i\}$ and $TM_\beta = \{\dot{y}^j(t_j) = dy^j/dt_j\}$.

Following [1], we use the modelling machinery consisting of:

1. Adaptive joint action (1)–(3) at the top-master level, describing the externally-appearing deterministic, continuous and smooth dynamics, and
2. Corresponding adaptive path integral (5) at the bottom-slave level, describing a wildly fluctuating dynamics including both continuous trajectories and Markov chains. This lower-level joint dynamics can be further discretized into a partition function of the corresponding statistical dynamics.

2.1 Adaptive joint action

By adapting and extending classical Wheeler–Feynman *action-at-a-distance electrodynamics* [8] and applying it to human co-action, we propose a two-term *psycho-physical action* (summation convention is always assumed):

$$A[x, y; t_i, t_j] = \frac{1}{2} \int_{t_i} \int_{t_j} \alpha_i \beta_j \delta(I_{ij}^2) \dot{x}^i(t_i) \dot{y}^j(t_j) dt_i dt_j + \frac{1}{2} \int_t g_{ij} \dot{x}^i(t) \dot{x}^j(t) dt$$

with $I_{ij}^2 = [x^i(t_i) - y^j(t_j)]^2$, where $IN \leq t_i, t_j, t \leq OUT$. (1)

The first term in (1) represents *potential energy of the cognitive/motivational interaction* between the two agents α_i and β_j .¹ It is a double integral over a delta function of the square of interval I^2 between two points on the paths in their Life–Spaces; thus, interaction occurs only when this interval, representing the motivational cognitive distance between the two agents, vanishes. Note that the cognitive (loco)motions of the two agents $\alpha_i[x^i(t_i)]$ and $\beta_j[y^j(t_j)]$, generally occur at different times t_i and t_j unless $t_i = t_j$, when *cognitive synchronization* occurs.

The second term in (1) represents *kinetic energy of the physical interaction*. Namely, when the cognitive synchronization in the first term takes place, the second term of physical kinetic energy is activated in the common manifold, which is one of the agents’ Life Spaces, say $M_\alpha = \{x^i(t_i)\}$.

The reason why we have chosen the action (1) as a macroscopic model for human joint action is that (1) naturally represents the transition map,

$$A[x, y; t_i, t_j] : \text{MENTAL INTENTION} \xrightarrow{\text{Synch}} \text{PHYSICAL ACTION},$$

from mutual cognitive intention to joint physical action, in which the joint action starts after the mutual cognitive intention is synchronized. In simple words, “we can efficiently act together only after we have tuned-up our intentions.”

Similarly, if we have the joint action of three agents, say α_i , β_j and γ_k (e.g., α_i in charge of acceleration, β_j – deceleration and γ_k – steering), we can associate each of them with an n D Riemannian Life–Space manifold, say $M_\alpha = \{x^i(t_i)\}$, $M_\beta = \{y^j(t_j)\}$, and $M_\gamma = \{z^k(t_k)\}$, respectively, with the corresponding tangent bundles containing their individual (loco)motion velocities, $TM_\alpha = \{\dot{x}^i(t_i) = dx^i/dt_i\}$, $TM_\beta = \{\dot{y}^j(t_j) = dy^j/dt_j\}$ and $TM_\gamma = \{\dot{z}^k(t_k) = dz^k/dt_k\}$. Then, instead of (1) we have

$$A[t_i, t_j, t_k; t] = \frac{1}{2} \int_{t_i} \int_{t_j} \int_{t_k} \alpha_i(t_i) \beta_j(t_j) \gamma_k(t_k) \delta(I_{ijk}^2) \dot{x}^i(t_i) \dot{y}^j(t_j) \dot{z}^k(t_k) dt_i dt_j dt_k$$

$$+ \frac{1}{2} \int_t W_{rs}^M(t, q, \dot{q}) \dot{q}^r \dot{q}^s dt, \quad (\text{where } IN \leq t_i, t_j, t_k, t \leq OUT) \quad (2)$$

with $I_{ijk}^2 = [x^i(t_i) - y^j(t_j)]^2 + [y^j(t_j) - z^k(t_k)]^2 + [z^k(t_k) - x^i(t_i)]^2$,

The triple joint action (2)² has a considerably more complicated geometrical structure than the bilateral co-action (1). It actually happens in the common $3n$ D *Finsler manifold* $M_J = M_\alpha \cup M_\beta \cup M_\gamma$, parameterized by the local joint coordinates dependent on the common time t . That is, $M_J = \{q^r(t), r = 1, \dots, 3n\}$. Geometry of the joint manifold M_J is defined by the *Finsler metric function* $ds = F(q^r, dq^r)$, defined by

$$F^2(q, \dot{q}) = g_{rs}(q, \dot{q}) \dot{q}^r \dot{q}^s, \quad (\text{where } g_{rs} \text{ is the Riemann metric tensor}) \quad (3)$$

¹Although, formally, this term contains cognitive velocities, it still represents ‘potential energy’ from the physical point of view.

²as well as its ND –generalizations

and the *Finsler tensor* $C_{rst}(q, \dot{q})$, defined by (see [9, 10])

$$C_{rst}(q, \dot{q}) = \frac{1}{4} \frac{\partial^3 F^2(q, \dot{q})}{\partial \dot{q}^r \partial \dot{q}^s \partial \dot{q}^t} = \frac{1}{2} \frac{\partial g_{rs}}{\partial \dot{q}^t}. \quad (4)$$

From the Finsler definitions (3)–(4), it follows that the partial interaction manifolds, $M_\alpha \cup M_\beta$, $M_\beta \cup M_\gamma$ and $M_\alpha \cup M_\gamma$ have Riemannian structures with the corresponding interaction kinetic energies,

$$T_{\alpha\beta} = \frac{1}{2} g_{ij} \dot{x}^i \dot{y}^j, \quad T_{\alpha\gamma} = \frac{1}{2} g_{ik} \dot{x}^i \dot{z}^k, \quad T_{\beta\gamma} = \frac{1}{2} g_{jk} \dot{y}^j \dot{z}^k.$$

2.2 Adaptive path integral

At the slave level, the adaptive path integral (see [1]), representing an infinite-dimensional neural network, corresponding to the adaptive bilateral joint action (1), reads

$$\langle OUT|IN \rangle := \int \mathcal{D}[w, x, y] e^{iA[x, y; t_i, t_j]}, \quad (5)$$

where the Lebesgue integration is performed over all continuous paths $x^i = x^i(t_i)$ and $y^j = y^j(t_j)$, while summation is performed over all associated discrete Markov fluctuations and jumps. The symbolic differential in the path integral (5) represents an *adaptive path measure*, defined as a weighted product

$$\mathcal{D}[w, x, y] = \lim_{N \rightarrow \infty} \prod_{s=1}^N w_{ij}^s dx^i dy^j, \quad (i, j = 1, \dots, n). \quad (6)$$

Similarly, in case of the triple joint action, the adaptive path integral reads,

$$\langle OUT|IN \rangle := \int \mathcal{D}[w; x, y, z; q] e^{iA[t_i, t_j, t_k; t]}, \quad (7)$$

with the adaptive path measure defined by

$$\mathcal{D}[w; x, y, z; q] = \lim_{N \rightarrow \infty} \prod_{S=1}^N w_{ijk}^S dx^i dy^j dz^k dq^r, \quad (i, j, k = 1, \dots, n; \ r = 1, \dots, 3n). \quad (8)$$

3 Chaos and Bernstein–Brooks Adaptation

From previous sections, we can see that for modelling a two-actor co-action the Riemannian geometry is sufficient. However, it becomes insufficient for modelling the joint action of 3 or more actors, due to an *intrinsic chaotic coupling* between the individual actors. In this case we have to use the Finsler geometry, which is a generalization of the Riemannian one. This corresponds to the well-known fact in chaos theory that in continuous-time systems chaos cannot exist in the phase plane – the third dimension of the system phase-space is necessary for its existence. This also corresponds to the well-known fact of life that a trilateral (or, multilateral) relation is many times more complex than a bilateral relation. (It is so in politics, in business, in marriage, in romantic relationships, in friendship, everywhere... Physicists would say that any bilateral relation(ship) between Alice and Bob is very likely to crash if Chris comes in between, or at least it

becomes much more complicated.) This is also related to Lotka–Volterra systems [20, 21], other competing systems [22] and predator–prey systems [23, 24], as well as interacting Morris–Lecar neurons [25].

The adaptive path integrals (5) and (7) incorporate the *local Bernstein adaptation process* [11, 12] according to Bernstein’s discriminator concept

$$\text{desired state } SW(t+1) = \text{current state } IW(t) + \text{adjustment step } \Delta W(t).$$

The robustness of biological motor control systems in handling excess degrees of freedom has been attributed to a combination of tight hierarchical central planning and multiple levels of sensory feedback–based self–regulation that are relatively autonomous in their operation [13]. These two processes are connected through a top–down process of action script delegation and bottom–up emergency escalation mechanisms. There is a complex interplay between the continuous sensory feedback and motion/action planning to achieve effective operation in uncertain environments (such as movement on uneven terrain cluttered with obstacles). In case of three or more actors, the multilateral feedback/planning loop has the purpose of *chaos control* [14, 15].

Complementing Bernstein’s motor/chaos control principles is Brooks’ concept of computational *subsumption architectures* [18, 19], which provides a method for structuring reactive systems from the bottom up using layered sets of behaviors. Each layer implements a particular goal of the agent, which subsumes that of the underlying layers.

For example, a robot’s lowest layer could be “avoid an object”, on top of it would be the layer “wander around”, which in turn lies under “explore the world”. The top layer in such a case could represent the ultimate goal of “creating a map”. In this configuration, the lowest layers can work as fast–responding mechanisms (i.e., reflexes), while the higher layers can control the main direction to be taken in order to achieve a more abstract goal.

The substrate for this architecture comprises a network of finite state machines augmented with timing elements. A subsumption compiler compiles *augmented finite state machine* descriptions into a special–purpose scheduler to simulate parallelism and a set of finite state machine simulation routines. The resulting networked behavior function can be described conceptually as:

$$\text{final state } w(t+1) = \text{current state } w(t) + \text{adjustment behavior } f(\Delta w(t)).$$

The Bernstein *weights*, or *Brooks nodes*, $w_{ij}^s = w_{ij}^s(t)$ in (6) are updated by the *Bernstein loop* during the joint transition process, according to one of the two standard neural learning schemes, in which the micro–time level is traversed in discrete steps, i.e., if $t = t_0, t_1, \dots, t_s$ then $t+1 = t_1, t_2, \dots, t_{s+1}$:

1. A *self–organized, unsupervised* (e.g., Hebbian–like [16]) learning rule:

$$w_{ij}^s(t+1) = w_{ij}^s(t) + \frac{\sigma}{\eta}(w_{ij}^{s,d}(t) - w_{ij}^{s,a}(t)), \quad (9)$$

where $\sigma = \sigma(t)$, $\eta = \eta(t)$ denote *signal* and *noise*, respectively, while new superscripts d and a denote *desired* and *achieved* micro–states, respectively; or

2. A certain form of a *supervised gradient descent learning*:

$$w_{ij}^s(t+1) = w_{ij}^s(t) - \eta \nabla J(t), \quad (10)$$

where η is a small constant, called the *step size*, or the *learning rate*, and $\nabla J(n)$ denotes the gradient of the ‘performance hyper–surface’ at the t –th iteration.

Both Hebbian and supervised learning³ are used in local decision making processes, e.g., at the intention formation phase (see [1]). Overall, the model presents a set of formalisms to represent time-critical aspects of collective performance in tactical teams. Its applications include hypotheses generation for real and virtual experiments on team performance, both in human teams (e.g., emergency crews) and hybrid human-machine teams (e.g., human-robotic crews). It is of particular value to the latter, as the increasing autonomy of robotic platforms poses non-trivial challenges, not only for the design of their operator interfaces, but also for the design of the teams themselves and their concept of operations.

4 Conclusion

In this paper we have applied the previously developed Life Space Foam approach to model the dynamics of co-action by two or more agents. This dynamics is modelled by:

1. a two-term adaptive joint action, including mental cognitive/motivational potential and physical kinetic energy, and
2. its associated adaptive path integral, representing an infinite-dimensional neural network.

Its feedback adaptation loop has been derived from Bernstein's concepts of sensory corrections loop in human motor control and Brooks' subsumption architectures in robotics. The presented model demonstrates that in case of trilateral or multilateral joint action we have the strong possibility of chaotic behavior. Potential applications of the proposed model in human-robot interaction research are discussed.

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³Note that we could also use a reward-based, *reinforcement learning* rule [17], in which system learns its *optimal policy*:

$$innovation(t) = |reward(t) - penalty(t)|.$$

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